Dawud Gordon,
Georg von Zengen,
Michael Beigl

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ActiVibe: Using a Vibration Sensor for Activity Recognition

Dawud Gordon, Georg von Zengen, and Michael Beigl

Technische Universitt Braunschweig,
Braunschweig 38106, Germany
{gordon,vonzeng,beigl}@ibr.cs.tu-bs.de
http://www.ibr.cs.tu-bs.de/users/gordon

Abstract. This paper researches a new approach to activity recognition using a novel sensor, a micro-vibration sensor based on a micromachined production process. The sensor is a miniaturized ball switch with a very high sensitivity which in some circumstances is as decisive as an accelerometer as to specific activities. For evaluation purposes, the sensor was worn in parallel with an accelerometer in order to exactly determine its capabilities and the results are compared with other accelerometer-based activity recognition implementations. We explore the properties of both sensors as context recognition tools and find that classification percentages are comparable when recognizing four activities (walking, running, bus, bike). We also compared power consumption based on measurements of the micro-vibration and acceleration sensors, along with data processing methods. We conclude that the substantially lower price (3x), smaller device size (2x), very competitive classification percentage possibilities (equal) and power consumption 50 times less than accelerometers make this sensor a very attractive alternative.

Key words: Activity Recognition, Ball Switch, Vibration Sensor, Context Recognition, Machine Learning, Pattern Matching

1 Introduction and Related Work

Intelligent devices are increasingly expected to recognize their environment and situations. The most common way of fulfilling these expectations is by using acceleration sensors which are rapidly becoming ubiquitous in modern day technology. They are embedded in devices from cell phones and laptops to every-day items such as tennis shoes and TV remote controls [2]. Their effects range from smart phones which are capable of adjusting themselves based on their orientation to devices that can recognize individual users and situations [2][10][6].

Several applications have already been developed which use multiple acceleration sensors at different body locations to recognize different activities, e.g. [8][9][5][1]. Other examples use one single sensor location but multiple sensory types to recognize a variety of activities such as daily routines in [10], or a broad spectrum of activities in [6][11][2]. The resulting systems can automatically recognize and adjust to certain situations and activities without the user having to explicitly input anything. These applications are usually mobile and therefore must be energy aware in order to avoid unnecessary maintenance activity such as battery replacement or charging. In this paper, a new approach to activity recognition is presented using a novel, low-power vibration sensor to recognize certain activities and situations while consuming significantly less power than an acceleration sensor. Our intended application case is an ultra-low-power sensor node running on a single CR1620 coin cell that is able to perform continuous activity monitoring using a vibration sensor.

This vibration sensor is a miniaturized ball switch (fig. 1), where a conductive sphere rolls between two charged plates, closing a circuit in a certain position. With a diameter of 0.8mm, the sphere's physical properties are different than those in traditional ball switches, especially in terms of sensitivity even at extremely low-intensity movements, as well as sensitivity in all three dimensions. The thesis of this paper is that the ball switch can be a equivalent replacement for 3-D accelerometers when performing activity recognition, while consuming less power. This is based on the assumption that higher time resolution possible with the vibration sensor will outweigh the better data resolution (3 analog vs. 1 binary value) of acceleration sensors. Ball switches have been used before to successfully classify activities in [9] and [10], but both approaches use multiple switches to interpret attitude and orientation information. The ActiVibe approach uses the output to directly classify activities. In [9] such an approach was attempted with multiple switch inputs to a spiking neural network with mediocre results.

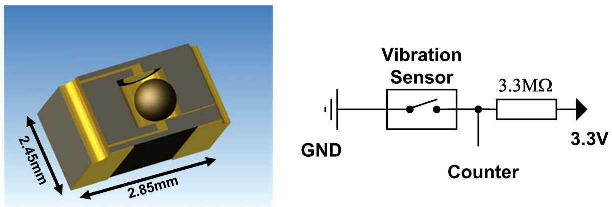

Fig. 1. The Micro Vibration Sensor from [3] and Schematic

2 Sensory Data Generation and Analysis

In order to evaluate the new activity recognition techniques using the vibration sensor, a sampling board was constructed which simultaneously gathered sensory data from a vibration sensor and an accelerometer. The experiment utilizes the Akiba sensor node which conducted measurements using an on board MVS0608.02 micro-vibration sensor (MVS) from Sensolute [3] and an external ADXL335 3D accelerometer (ADXL) from Analog Devices [4]. Each axis of the ADXL is directly connected to one of the 10bit-wide A/D ports of the processor (Microchip PIC18LF14K22), and the MVS output is connected to the 16bit timer1 input. This constellation allows A/D conversion and counting to run independently of the processor. The node conducted readings from both A/D (ADXL) and timer1 (MVS) registers at a frequency of 100Hz and outputted the measurements to a laptop via a serial line connection. The sampled data was then logged on the laptop for further analysis.

2.1 Data Preprocessing

Unlike the signal produced by the analog acceleration sensor, the output of the MVS is a digital binary vector as can be seen in fig. 2, 1). The interesting information from these signals are the unary transitions between the two states of the signal. The actual vibration data is a time-series of sequential events whose only important unit is their time stamp, or position on the time line. We refer to these events as ticks. Ticks are signaled by a change in voltage on the output pin of the vibration sensor, from zero to a logical one or one to zero.

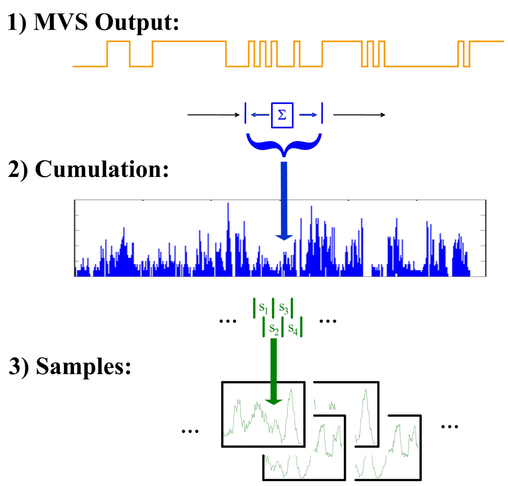

Fig. 2. The preprocessing algorithm for the MVS sensor output

In order to be able to recognize a specific pattern within this system, namely a pattern generated by a certain activity, this signal must be converted into a form which can be analyzed using algorithms from the fields of data mining and context recognition. To create such a signal from the time-series, a cumulation function was implemented which creates an analog wave form from the individual events. This function uses a history window to construct a wave based on the number of events in that window. The window is passed over the time line creating a new signal as depicted in figure 2, 2). In figure 2, 3), this wave is cut into separate samples to be classified as to the activity being performed by the recognition algorithm.

2.2 Activity Recognition

The WEKA data mining toolkit [12] was selected for the recognition of activities within the sensory data streams for its simplification of the pattern-matching algorithms. Specifically the C4.5 decision tree [7] was used due to its prevalence in the activity recognition literature using acceleration sensors [8][6][1] and its suitability for the intended ultra-low-resource sensor node platform. For this reason, a direct comparison with current results from other publications is possible without having to verify the viability of the pattern matching algorithms.

Using the samples generated by the algorithm in fig. 2, 3), a set of features is generated for each sample which is used to identify the activity. The features used are identical for both sets of data, except for the fact that the acceleration data uses additional features indicating the direction in which the acceleration occurred. This information is not available when using the vibration sensor as only one sensor is being used and the axis of a specific vibration is very difficult to isolate and is not a part of this work. The acceleration sensor on the other hand is equipped with 3 different axes, or is three sensors in one, and therefore can measure activity properties which are beyond the scope of the ball switch. The other features generated are mean, standard deviation, entropy, area under the curve and FFT-peaks, since these were often cited as being the most decisive [1][5][11][8][6].

The C4.5 decision tree was constructed and trained by the WEKA toolkit using the activity feature sets for the vibration data on the one side and the acceleration data on the other. This was done in parallel for both data sets, where the sensors were subjected to the same conditions during the performance of each activity. The total data is divided in half where one part is used for training purposes and the other for testing of the classification algorithm.

3 Sensor Hardware Comparison

The ADXL-335 3D acceleration sensor was chosen because of its ease of use as well as its typical power consumption signature. In the data sheet the current drawn by the sensor is indicated to be close to $425\mu A$ at an operating voltage of $3.3V$. At that voltage the rate of consumption of the ADXL is $P_{ADXL} = 1.4mW$. The schematic for the integration of the MVS 0608.02 shown in figure 1 implements a $3.3M\Omega$ pull-up resistor and therefore pulls a total current of $1\mu A$ at $3.3V$. This yields a calculated consumption of $P_{MVS-calc} = 3.3\mu W$.

The MVS has two states as with any switch: `ON` and `OFF`. In the `ON` state the consumption is $P_{MVS-calc} = 3.3\mu W$, but in the `OFF` state the consumption is virtually zero, since no current flows over the sensor. Due to the construction of the MVS, the sensor is in either state at any given time with a probability of 50%, meaning that the actual consumption is only half of the calculated consumption, or $P_{MVS} = P_{MVS-calc}/2 = 1.45\mu W$. This is approximatley one full order of magnitude less than that of the acceleration sensor.

3 ADC operations are necessary to convert the measured acceleration for each ADXL axis represented in voltage to a digital value, each costing $1.2ms$

giving a total of $3.6ms$ when the PIC18LF14K22 is in low power mode clocked at 31.25kHz. Each ADC read requires 2 `MOV` commands to transfer the 10 bit values from the SFR to memory, each costing 1 processor cycle, yields 12 processor cycles. Each processor cycle requires 4 clock cycles yields a total $1.536ms$ per ADC read. Together, converting an analog value to a digital one and transferring it to specific location costs $T_{ADXL} = 1.536ms + 3,6ms = 4.368ms$. Vibration readings and cumulation are directly carried out by a hardware component of the processor, the timer/counter. This is a module which operates at extremely low power, independent from the rest of the embedded processor. Reading this value, checking and accounting for overflow and subtracting the previously read value incurs on average 64 clock cycles which requires $T_{MVS} = 8,192ms$ at $31.25kHz$.

As the processor pulls $15.5\mu A$, its power consumption is $P_{proc} = 51.15\mu W$ at $3.3V$. One accelerometer measurement lasts $T_{ADXL} = 4.368ms$ with a consumption rate of $P_{proc} + P_{ADXL} = 1.45115mW$. For the vibration sensor, one reading uses a total of $P_{proc} + P_{MVS} = 54.45\mu W$. This indicates that the energy required to sample the MVS is approximately 14 times less than that necessary to sample the acceleration sensor. The validity of these calculations will be confirmed later in section 4.2.

The physical size of both sensors is also comparable; the MVS has a footprint of $2.45mm$ x $2.85mm$ where the ADXL sensor is slightly larger at $4mm$ x $4mm$. Both sensors require external circuitry in order to operate properly; the MVS requires one resister where the ADXL uses 3 capacitors, one for each axis.

Another difference between the two sensors is the cost. The ADXL335 is one of the more costly acceleration sensors at about 5.50 USD with other comparable models priced as low as 3.00 USD. The MVS on the other hand is a far simpler sensor and is therefore less expensive. The current cost of an MVS0608.02 sensor is approximately 1.75 USD, so the sensor is quite competitive, even at the lower end of the acceleration sensor pricing. On a side note, the MVS requires a counter input pin from the processor while the ADXL uses 3 A/D processor inputs.

4 Evaluation and Results

In the course of this initial evaluation, 4 different activities were classified using both the vibration and acceleration sensors. The activities were walking, running, riding a bicycle and riding a bus, with a total of approximately 10 minutes per activity gathered by an evaluation user. The data was gathered using an Akiba sensor node (18x17x8mm incl. bat., PIC18LF14K22, CC2500) which sampled both sensors in parallel at a rate of 100Hz during the course of these different activities. The sensor node was worn by the user at the waist/belt which has been indicated as the optimal location for an acceleration sensor in [1]. The samples were outputted directly to a laptop computer carried in a backpack via a serial cable as can be seen in figure 3.

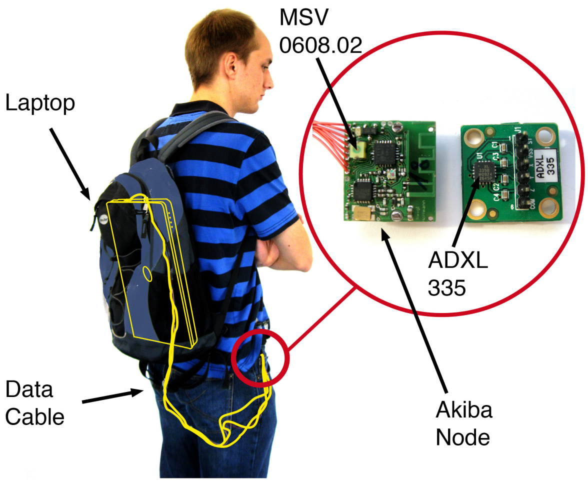

Fig. 3. The test subject with sensor node, data cable and laptop computer

4.1 Classifier Performance

The data used in this initial evaluation was gathered by a single user in a controlled experiment. In total, approximately 10 minutes of data for each activity was used. In order to find the optimal preprocessing settings for the vibration sensor, the cumulation window length was varied giving the optimal settings for activity recognition. The cumulation window was implemented by a hardware counter on the microprocessor with an optimal window length of 10ms at a sample rate of 100Hz. With the cumulative window set, the sample length was optimized for the MVS data. A maximum was found at a sample length of 1.05 seconds with a recognition rate of 99.77%. The sampled data of the ADXL sensor does not require preprocessing and can therefore be cut directly into samples over which the features are calculated. The results of this process indicate a maximum at 0.65 seconds with a recognition rate of 99.55%. Table 1 displays the confusion matrices for both sets of data, where the rows are the different activities and the columns indicate how the sample was classified. These recognition rates are far higher than all rates achieved in the related work. This can be contributed to the low number of activities classified as well as the non-natural test environment used to generate samples (see section 5: Conclusion). On the other hand, the fact that recognition rates for the MVS are slightly better than for the accelerometer support the thesis outlined in this paper.

4.2 Power Measurements

In order to confirm the calculations done in section 3, measurements were conducted using a BBC Goerz Metrawatt measurement device in a laboratory setting. Each sensor was connected and sampled individually in an endless loop

	MV Sensor				ADXL Sensor			
Activity	a	b	c	d	a	b	c	d
a = Walking	99.1	0	0	0.9	99.4	0	0	0.6
b = Running	0	100	0	0	0	100	0	0
c = Bus	0	0	100	0	0	0	100	0
d = Bike	0	0	0	100	0	1.2	0	98.8

Table 1. Confusion matrix for classification of data samples, values in percent

under heavy agitation to mimic activity under real conditions. Current flow was measured during this process in order to quantify power consumption over a time period under these circumstances. Processor activities performed for the ADXL and MVS were as described in sections 2.1 and 3. In one cycle (sensor measurement, subsequent processing), an average current flow of $630\mu A$ for the ADXL, and $12.8\mu A$ for the vibration sensor was measured. At 3.3V this yields power consumption rates of ca. $2.08mW$ for the ADXL ($172.8J$/day) and $42.24\mu W$ for the MVS ($3.5J$/day). The lifetime with a watch-type coin cell (CR1620, $1kJ$) would equate to 6 days using the ADXL and 285 days using the MVS in worst case when assuming 24/7 activity of the user. These results show that the MVS would reduce the total measured consumption of the sensor node system by a factor of almost 50 when compared to the ADXL. The difference between the calculated and measured values (MVS: $2.08mW$ vs. $1.45mW$ and ADXL: $0.04mW$ vs. $0.054mW$) can be explained by the difference between the consumption rates of the processor, A/D and timer unit in the preliminary data sheet and that which was measured, which can either be attributed to measurement device calibration or a documentation error.

5 Conclusion

In this paper, a novel type of sensor was introduced into the field of activity recognition. We presented a novel method for generating sample and feature information from this sensor and evaluated the approach for activity recognition. Our thesis was, that this sensor is comparable to acceleration sensors for activity recognition due to its higher time resolution in capturing movement events than existing acceleration sensors. We confirmed the thesis and also showed via calculation and measurements that the vibration sensor solution shows impressively lower power consumption: The proposed activity recognition solution would be able to run for over a year with a small CR1620 battery (6 days with acceleration sensor). At the same time the sensor is not as powerful when it comes to sensing the direction of an activity, although this does not appear to adversely affect activity recognition rates in our studies so far.

Currently, work is being done to expand on and finalize the initial results presented here. Multi-user trials with 12 activity classes are scheduled in order to better evaluate the strengths and weaknesses of the accelerometer and the micro vibration sensor. With these studies we seek to understands the limits and potentials of the sensor in complex activity recognition tasks better. At the same time the activity recognition methods developed in ActiVibe are being ported to run on the Akiba sensor node hardware. This will allow ultra-low-power classification at runtime as well as long-term non-intrusive trials which will indicate the applicability of these results to real-world situations and test power consumption of longer time periods.

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